



Detecting land-use/land-cover change in rural–urban fringe areas using extended change-vector analysis

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ABSTRACT

Detecting land-use/land-cover (LULC) changes in rural–urban fringe areas (RUFAs) timely and accurately using satellite imagery is essential for land-use planning and management in China. Although traditional spectral-based change-vector analysis (CVA) can effectively detect LULC change in many cases, it encounters difficulties in RUFAs because of deficiencies in the spectral information of satellite images. To detect LULC changes in RUFAs effectively, this paper proposes an extended CVA approach that incorporates textural change information into the traditional spectral-based CVA. The extended CVA was applied to three different pilot RUFAs in China with different remotely sensed data, including Landsat Thematic Mapper (TM), China–Brazil Earth Resources Satellite (CBERS) and Advanced Land Observing Satellite (ALOS) images. The results demonstrated the improvement of the extended CVA compared to the traditional spectral-based CVA with the overall accuracy increased between 4.66% and 8.00% and the kappa coefficient increased between 0.10 and 0.15, respectively. The advantage of the extended CVA lies in its integration of both spectral and textural change information to detect LULC changes, allowing for effective discrimination of LULC changes that are spectrally similar but texturally different in RUFAs. The extended CVA has great potential to be widely used for LULC-change detection in RUFAs, which are often heterogeneous and fragmental in nature, with rich textural information.

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1. Introduction

The rural–urban fringe area (RUFA) is often defined as the landscape located just outside established cities and towns, where the countryside begins (Sullivan and Lovell, 2006). Since the launch of economic reforms and open-door policies in the late 1970s, China has experienced unprecedented urbanization, resulting in rapid and sustained land-use/land-cover (LULC) changes in RUFAs (Liu et al., 2007). Such human-induced changes, characterized by shifts from natural to artificial land covers, have complicated impacts on air pollution, biodiversity, and runoff and evapotranspiration processes (Clarke et al., 1997).

Inventorying and monitoring of LULC changes is essential for land-use planning and management in China's rapidly changing RUFAs. Remote sensing is a useful technology for LULC mapping and change detection, providing advantages of frequent revisit, global coverage, and low cost (Zhang et al., 2003). Over the past

two decades, a number of approaches for LULC-change detection using satellite imagery have been formulated, applied, and evaluated; these can be broadly grouped into three general types (Coppin et al., 2004; Dewan and Yamaguchi, 2009; Lu et al., 2004; Singh, 1989): (1) those based on classification of input data, such as post-classification comparison (Yuan et al., 2005) and direct two-date classification (Carreiras et al., 2006; Lucas et al., 2000); (2) those based on spectral change between two acquisition dates, including band algebra methods (Townshend and Justice, 1995), regression analysis (Fraser et al., 2005), principal component analysis (Hartter et al., 2008), and change-vector analysis (CVA) (Bayarjargal et al., 2006; Lambin and Strahler, 1994); and (3) those based on the objects composed of adjacent pixels with similar spectra (Bontemps et al., 2008; Desclee et al., 2006). Studies have shown that different methods have their own merits and that no single approach is optimal and applicable to all cases (Bontemps et al., 2008; Conchedda et al., 2008; Dewan and Yamaguchi, 2009). Selection of an appropriate change-detection approach, in practice, often depends on the information requirements, data availability and quality, time and cost constraints, and the analyst's skill and experience (Chen et al., 2003).

Among the spectral change-based approaches, CVA has a few advantages: it not only can avoid shortcomings of classification-

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based approaches such as cumulative error in image classification for individual dates, but also can detect change using all bands and provide “from-to” change information (Chen et al., 2003). In recent years, the advantages and potentials of CVA have been demonstrated in studies documenting urban sprawl and updating LULC data (Chen et al., 2003; Xian et al., 2009).

However, RUFAs are often heterogeneous and fragmental in nature, with intensive anthropogenic activities (Sullivan and Lovell, 2006). They may include different land-cover types, such as concrete, asphalt, trees, grass, water, soil, and various kinds of roof materials, which have different radiometric characteristics in a remotely sensed image. Defining a land-use class based on spectral homogeneity is often difficult in RUFAs because some land-use categories are often spectrally similar to other land-use types. Thus in the case of change detection in RUFAs, large spectral differences between two dates do not necessarily indicate LULC change. At the same time, the spectral response may be close even if LULC change has occurred. As a spectral-based change-detection approach, CVA can often perform well when a situation satisfies the assumption that changes on the ground cause significant changes in image pixel values and that these spectral changes reflect mostly changes on the ground rather than differences produced by atmospheric and other system variations (Singh, 1989). However, spectral information alone is not sufficient for representing LULC in RUFAs based on remotely sensed data. The spectral-based CVA encounters difficulty in detecting LULC change in RUFAs (Chen et al., 2003; Zhang et al., 2002).

Texture refers to the tonal or gray-level variations in an image (Pacifi et al., 2009). Because texture reflects the distribution and variation of neighborhood pixel values, it is regarded as an important factor that can compensate for deficiencies in spectral information in satellite imagery analysis (Carleer and Wolff, 2006). For example, Gong et al. (1992) demonstrated that textural information was useful for resolving spectral confusion between land-cover classes. In addition, Jensen and Toll (1982) found that combined spectral-textural image differencing provided better change-detection results using Landsat Multi-Spectral Scanner data. With the consideration of the rich texture information in RUFAs, the addition of the texture information to the spectral-based CVA can detect the LULC in RUFAs more effectively.

To effectively detect the LULC changes in RUFAs, this paper presents an extended CVA approach that combines texture information into the traditional spectral-based CVA. The extended CVA approach was applied and validated by three different pilot RUFAs in China with different remotely sensed data acquired by Landsat Thematic Mapper (TM), China-Brazil Earth Resources Satellite (CBERS) and Advanced Land Observing Satellite (ALOS), respectively. The remainder of this paper introduces the extended CVA approach and presents a detailed description of the application of the extended CVA in different pilot areas.

2. Methodology

2.1. Traditional spectral-based CVA

Malila (1980) presented the general concept of the spectral-based CVA. A change vector can be described by the angle of change (vector direction) and the magnitude of change from dates 1 to 2 (Johnson and Kasischke, 1998). If a pixel's gray-level (spectral) values in two images acquired on dates t_1 and t_2 are represented by $G = (g_1, g_2, \dots, g_k)^T$ and $H = (h_1, h_2, \dots, h_k)^T$, respectively, and k is the number of spectral bands, a change vector can be defined as

$$\Delta G = G - H,$$

where ΔG represents all the change information between the two dates for a given pixel. The change magnitude $\|\Delta G\|$ can be calculated by

$$\|\Delta G\| = \sqrt{(g_1 - h_1)^2 + (g_2 - h_2)^2 + \dots + (g_k - h_k)^2} \quad (2)$$

which represents the total gray-level (spectral) difference between the two dates. The greater $\|\Delta G\|$ is, the higher the possibility of change is. Thus a decision on change is made based on whether the change magnitude $\|\Delta G\|$ exceeds a specific threshold determined by qualitative or quantitative analysis. The type of change is often identified using the vector angle in two spectral dimensions or using sector codes if more than two spectral dimensions are involved (Chen et al., 2003). The geometric concept of CVA is applicable to any number of spectral bands, no matter what measurement scale of radiance is used (Johnson and Kasischke, 1998).

2.2. Extended CVA

Unlike the traditional spectral-based CVA, the basic idea of the extended CVA approach is to add textural information to the traditional spectral-based CVA so that some LULC changes that are spectrally similar but texturally different in RUFAs can be effectively detected. Specifically, the extended CVA includes three major steps. The first step is to produce the textural bands by texture calculation and normalization. The second step is to produce the two-band extended change-magnitude image including spectral change information and textural change information simultaneously. The third step is to extract the changed pixels by the support vector machine (SVM) approach. Fig. 1 shows the comparison between the traditional CVA (Fig. 1a) and the extended CVA (Fig. 1b).

2.2.1. Producing textural bands

Many methods are available for extracting texture information from satellite imagery. Previous studies (Arzandeh and Wang, 2002; Shanmugan et al., 1981) reported that the most effective approach was to calculate texture statistics based on the gray-level co-occurrence matrix (GLCM) proposed by Haralick (1973). The GLCM is derived from the gray-level image that shows the joint probability distribution of a pair of gray levels, separated at a certain distance and a certain orientation. Eight texture features based on the GLCM method are widely used, including homogeneity (HOM), contrast (CON), dissimilarity (DIS), MEAN, standard deviation (SD), entropy (ENT), angular second moment (ASM), and correlation (COR) (Zhang et al., 2003). Detailed definitions of the abovementioned eight GLCM texture features have been provided by Haralick (1973). However, it is not necessary to use all eight GLCM texture features simultaneously to produce the texture bands in the extended CVA, considering their information redundancy. According to Hall-Beyer (2007), the eight GLCM textural parameters can be classified into three groups: the ‘contrast’ group (CON, DIS, and HOM), the ‘orderliness’ group (ASM and ENT), and the ‘descriptive statistics’ group (MEAN, SD, and COR). CON, DIS, and HOM in the ‘contrast’ group are correlated with one another, as are ASM and ENT in the ‘orderliness’ group; however, MEAN, SD, and COR in the ‘descriptive statistics’ group do not show obvious correlation. Here, five texture features (CON, ASM COR, MEAN, and SD) were selected to produce the five texture feature images. For the five derived textural bands to have the same value range as the spectral bands of the Landsat TM images, the following standardization procedure was applied:

$$DN' = \frac{DN - DN_{\min}}{DN_{\max} - DN_{\min}} \times 255, \quad (3)$$

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